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Lateral inventory share-based models for IoT-enabled E-commerce sustainable food supply networks

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ABSTRACT

This research investigates lateral inventory share-based business models for e-grocery networks where online groceries are inter-connected in an Internet of Things (IoT) environment. Recently, managing food supplies has become a very important issue due to the onset of unexpected conditions such as natural disasters (earthquakes, tsunamis, floods, droughts etc.) and pandemics. In this paper, we aim to design sustainable food supply chain networks for e-commerce food companies (e.g. e-groceries) by applying lateral inventory share policies after the consideration of the existence of strategic alliances between organizations. We aim to minimize food waste as well as back orders resulting in more sustainable networks. Further, we explore how a business-to-business (B2B) policy (i.e. lateral-inventory share policy) should be designed to optimize business (i.e. e-groceries) profitability. We optimize the re-order and up-to (s, S) inventory levels of e-groceries for the pre-defined sharing policies by using a simulation optimization approach. The optimal results show that having a lateral inventory share poliIndiacy in food networks is more efficient compared to a non-lateral policy. Also, at the optimal points of the considered policies, lateral inventory share ratio is usually observed to be larger than 50% on average, meaning that more than half of customer orders are met by lateral inventory share.

1. Introduction

The recent Covid-19 pandemic has affected our lives significantly. During lockdowns, managing e-commerce to ensure safe and sufficient food supplies has become one of the most critical issues for society. For instance, Singh et al. (2020) declare that two essential items, food and medical equipment, must be made available during the pandemic. Moreover, it has also been observed that all kinds of food chains, such as perishable products, fresh vegetables, fruits, bakery items etc. have been significantly affected by the Covid-19 outbreak (Ivanov et al., 2020; Ivanov et al., 2019; Scheibe and Blackhurst, 2018). Hence, efficient management of food supply networks resulting in decreased food waste and increased sustainability for e-commerce food companies (e.g. supermarkets) has become one of the key deliverables. To achieve this goal, food supply chains need to become much faster, more transparent and highly connected. Hence, digitisation of the network becomes a crucial aspect for companies in such situations (Supply Chain 4.0, 2016). Given recent technological developments (e.g. sensors, robotics, actuators etc.), companies are seeking to manage such transformations in their supply chains. By the digitisation of a supply chain network, the supply chain 4.0 concept can deliver a faster, flexible, granular, accurate, transparent, efficient and more sustainable network (Supply Chain 4.0, 2016).

SC 4.0 paves the way for the development of new business models to increase supply-chain flexibility. Rather than maintaining resources and capabilities in-house, companies can invest in relationships with other organizations to source multiple providers of components, thus helping to spread some of the capital risk. Such a partnership can also provide increased market share, inventory reductions, improved delivery service, improved quality and shorter product development cycles. Strategic alliance is a

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partnership realized between two or more organisations. Agreements inherent in a strategic alliance ensure that stages are managed with consideration of the welfare of others in mind; companies should not change or use stages for their own advantage without considering the impact on other organisations involved. Some strategic alliance resources are: products, distribution channels, manufacturing capability, knowledge etc. For instance, the relationship among Dell, Sony and Airborne is a strategic alliance. When Dell places the required orders for computers it assembles, it also orders the monitors that Sony manufactures. Airborne picks up computers from the Dell warehouse in Texas as well as monitors from the Sony warehouse in Mexico. It then merges the two and sends a combined order to the customer. Inventory share policy implemented towards strategic alliance is also known as lateral inventory share, inventory pooling or inventory trans-shipment in current literature. By working in this way, companies increase their flexibility, especially in emergency conditions where there may be a lack of resources (Lau et al., 2016). The reason why lateral inventory share becomes important is also due to the decreased product end-of-life cycle; keeping those products in an inventory adds cost to the wholesalers and manufacturers. Furthermore, in a food supply network, the perishability of products and inaccuracy of demand forecast leads to uncertainty in inventory management. The combination of all of these challenges has led organisations to redesign their supply chains towards considering inventory share policies.

Over the past few decades, the number of products in the market has largely increased (Mangal and Chandna, 2009; Li et al., 2020a,b) with the effects of e-commerce. The adoption of e-commerce has apparently become inevitable in distribution channels (Webster et al., 2006; Li et al., 2019a,b). For instance, due to the latest pandemic, online grocery has been brought to the fore (Keyes, 2020). Therefore, how online grocers can maximize their performances during and after the pandemic with innovations such as automation, operational flexibility and bundling services are still significant research subjects. When the product is a perishable food, preserving and maintaining the quality of the product while enhancing its logistic performance are essential.

This study aims to present business models for digitised food companies supported by digital technologies in an IoT environment to manage a sustainable food supply chain by adopting lateral-inventory share models. The main purpose of this paper is to help minimize food waste and increase sustainability by efficient management of food inventory in e-commerce food companies. In this sense, business-to-business (B2B) inventory policies (i.e. lateral-inventory share policies) are investigated to optimize the profitability of each business, while preventing food waste in a digital economy. The study addresses the following research questions (RQs):

RQ1: How does lateral-inventory share (LIS) contribute to a sustainable food supply chain?.

RQ2: How does digitalisation (IoT) contribute to a sustainable food supply chain?.

The main motivation underlying this paper is to tackle the rising food waste issue and accordingly effective waste management of food supply chains e.g. inventory management, sustainable food networks, waste elimination etc. Food waste is an issue that is becoming increasingly important and needs to be addressed. However, with the effects of the Covid-19 pandemic, e-commerce, especially e-grocery, has seen a remarkable increase. Also, issues such as adequate and safe food supply have become more important with the effect of the Covid-19 pandemic. With this in mind, lateral trans-shipment is proposed as a solution to this problem; the effects of lateral inventory sharing and digitalisation on the sustainable supply chain must be investigated in order to address the relevant food waste problem accelerated by Covid-19.

In this paper, three different B2B scenarios based on lateral inventory share policies are considered; an examination of minimization of total food waste in the food supply network will address RQ1. By simulating a digitised e-commerce food network, where online groceries can share their existing inventory information with their same echelon level food companies resulting in decreased food waste and ordering frequency (e.g. transportation frequency) will address RQ2.

To the best of our knowledge, this paper is an initial attempt in studying inventory share-based B2B models for e-grocery networks where customer orders are shipped to the customer locations directly without making a physical lateral trans-shipment to another online grocery. In addition, optimizing each pre-defined inventory share policy under (s, S) inventory control model considering minimization of average inventory carried in the network under different designs of ordering frequency from the main depot as well as shelf life of food products (i.e. tight and large) resulting in decreased food waste and increased sustainability in the network, we further aim to contribute to the sustainability of e-commerce food supply chains.

This study is structured as follows. In Section 2 literature related to lateral-inventory share, lateral-transhipment, food supply chain and IoT are examined. In Section 3, methodology, along with lateral-inventory share scenarios, is discussed. Section 4 analyses the results and provides relevant discussions. Finally, Section 5 provides the conclusion.

2. Literature review

There are a few studies focused on lateral inventory share problems. For example, Ekren and Arslan (2020) investigated inventory sharing in lateral trans-shipment issues with innovative technology such as real-time visibility of a supply network. With the help of these technologies, cost minimization can be achieved in inventory sharing between stocking locations. Accordingly, simulation models have been developed with total costs compared under pre-defined fill rate by using an optimization tool. Lateral inventory share problems are also modelled by Ekren and Heragu (2008) in physical lateral trans-shipment cases between stocking locations. However, those studies do not consider food products or the expiration date constraints of products. Further, in those studies, there is no online purchasing. Hence, physical trans-shipment of products between stocking locations takes place in these inventory share processes. A recent work is completed by İzmirli et al. (2020). They study an omni-channel network where online and offline stores are connected so that they can share their inventories among stores to provide better service for customer. Besides, Firouz et al. (2017) touched on a different problem about lateral trans-shipment which is the problem of integrated supplier selection and inventory with multi-sourcing. Hereby, the heuristic algorithm, decomposition-based and powered via simulation, has been generated to address the problem and provide a solution. Paterson et al. (2011) critically examined the existing literature about the inventory models for lateral trans-shipments. Rabbani et al. (2018) also suggested a heuristic, theoretical-based graph algorithm to address a multi-echelon responsive supply chain channel design with lateral trans-shipments. For this purpose, graph theory has been conducted to examine the supply chain network structure.

The main issue in the food supply chain is to preserve the quality of the product by improving its logistics performance. For that reason, many studies discuss about inventory routing problems for food supply chain. For example, Manouchehri et al. (2020) proposed a routing model for perishable products concerning "temperature" issues (storage and vehicle temperature). To address this, a hybrid search algorithm has been simulated and presented. Hartl and Romauch (2016) studied the single route lateral trans-shipment problem by using a mixed-integer linear program. In addition to that, the load capacity for generating an optimal solution is also considered and discussed. Rohmer et al. (2019) studied the two-echelon inventory routing problem for perishable products to minimize the overall transportation and holding cost. The problem has been formulated and modeled via a mixed-integer linear program and applied to a two-stage metaheuristic with a combination of adaptive large neighborhood search (ALNS) and a mixed integer linear programming (MILP) formulation. In addition to that, Soysal et al. (2018) analyzed the Inventory Routing Problem (IRP) with multiple suppliers and customers in terms of horizontal collaboration advantages in transportation operations and logistics cost; they addressed perishability, energy usage and uncertainty in demand issues. Hence, IRP has been modeled and analyzed by looking at various distribution structures for address related issues. Furthermore, Alkaabneh et al. (2020) addressed the inventory routing problems of perishable products in order to identify near-optimal replenishment scheduling and vehicle routes; the aim was to maximize the profit of the supplier and minimize the fuel, inventory holding costs and greenhouse emissions. Thus, Benders decomposition and a two-stage metaheuristic have been presented in two algorithms to solve the problem. Zhi and Keskin (2018) also studied on a multi-product, three-stage network with direct and lateral trans-shipments to determine the highest effective network configuration to reduce the overall fixed facilities and transport costs. Two solution algorithms centered on simulated heuristics of the annealing and GRASP were suggested.

As a solution to these lateral trans-shipment problems, Lau et al. (2016) suggested five lateral trans-shipment decision principles with a case-based guideline. At the end of the study, two-step lateral trans-shipment decision rules are presented to generate a roadmap for practitioners as a feasible solution to the problem. The feasibility and effectiveness of the proposed model have been ensured and verified by using Matlab. Tlili et al. (2012) suggested an inventory system generally focused on three parts: the inventory management model, the trans-shipment policy and the rationing policies as a solution. Therefore, an inventory model depending on this three-component system has been used to optimize the inventory model, trans-shipment policy and rationing policies. In addition to that, empirical simulation has been carried out for the validation of the model. Mogre et al. (2009) suggested that accurate visibility is a requirement for the adoption of lateral trans-shipment policy in warehouses and stores and that radio frequency identification (RFID) technology can provide such visibility. Therefore, this study aims to present an analytical model that discusses the main managerial implications that lateral trans-shipment replenishment policy, powered by RFID technologies, can offer. Salehi et al. (2015) suggested an effective heuristic-based memetic algorithm by designing a non-linear mixed-integer programming model in the context of a lateral trans-shipment analysis within an inventory network. The study proposes a design for the network of distribution in order to find the optimum numbers, location-allocation, capacities of retailers, etc. Nakandala et al. (2017) suggested a lateral trans-shipment design that integrates distortion cost in the total inventory cost with other factors related to perishable products; this involves transactions by a standard manufacturer, lateral trans-shipment, back order and storage, helping to improve the trade-off between these main cost factors. As a consequence, the lateral trans-shipment (LT) model involving related cost components has been proposed. Mercer and Tao (1996) studied alternative inventory and distribution policies of a food manufacturer as a solution to lateral trans-shipment problems. Also, Mangal and Chandna (2009) suggested that lateral trans-shipment can be used as an emergency supply for cases such as stock out and shortage to overcome the uncertainties in cost, demand and lead-time related to customer satisfaction and cost reduction. Therefore, a simple and intuitive model is proposed that proposes optimal inventory and policies for trans-shipment in 'n' locations. Some of these studies were focused on building business models and modeling programs that try for the optimization of the supply and demand balance problems in lateral trans-shipment with multi-location and multi-suppliers by using multi-echelon inventory models. For instance, Meissner and Senicheva (2018) pointed out the significance of lateral trans-shipments in terms of multi-location inventory systems to find an optimal policy that specifies the destinations of trans-shipments to maximize profit. Thereby, multi-location inventory systems are studied by using forward approximate dynamic programming under periodic review to establish a near-optimal trans-shipment policy. Also, Yan and Liu (2018) used the system dynamics approach to construct an inventory trans-shipment model focused on multi-echelon supply chains, including suppliers, distributors and retailers. Their analysis revealed that the average stock level has been moderately adjusted and deteriorated from the single to four-chain product trans-shipment models. Therefore, analysis has been conducted with single, double, three and four-chain inventory trans-shipment models with different levels by using simulation. Yan et al. (2019) generated a two-echelon and multi-location optimal inventory model that tries to make a match between supply and demand balance in lateral trans-shipments and emergency shipments in order to respond to the stock outs on time. Further, Avci (2019) carried out a simulation-based optimization of a retail network of several distribution centers and retailers. They examined the impact of lateral trans-shipment and accelerated shipments on supply chain efficiency under various disturbances. Amiri et al. (2020) presented a framework by considering a two-echelon supply chain network (multiple buyers and one vendor) about perishable products to find the sales quantity and estimate the level of inventory among vendors and buyers. The study focuses on perishable products because they have a short life cycle; thus, it requires consideration of different factors in terms of supply management and logistics network. Accordingly, the delivery, cost and sale determination of perishable products is a problem that needs careful consideration.

Apart from that, Nakandala et al. (2020) examined supply chain connections from a retailer's viewpoint in an industrialized, local fresh food process. A multiple case study approach has been carried out throughout the study to obtain data from twelve urban and local food retailers via interview with the data examined by using thematic analysis. Chernonog (2020) focused on the two-echelon of the supply chain as a manufacturer and a retailer to investigate the indirect implications of perishable food inventory by analyzing a Stackelberg game. Li et al. (2019c) explored a compromise model across the advantages and disadvantages of the retailer's lateral trans-shipment behavior, offering realistic perspectives into the lateral trans-shipment stock control issue. Van Wijk et al. (2019) also focused on a two stock-point inventory model that allows for lateral trans-shipment components among stock-points. For this purpose, the structure of the optimal lateral trans-shipment policy has been characterized and modeled in order to satisfy demands and to minimize average operating costs by using stochastic dynamic programming.

In addition, the effect of the lateral trans-shipment inventory model on the food supply chain has been examined by many studies. Reza Nasiri et al. (2015) studied the lateral shipments' effects on location, allocation and inventory decisions of distribution network centers. For this purpose, a non-linear mixed-integer programming model is conducted; this revealed that lateral trans-shipment can develop higher supply chain performance in terms of system costs, safety stock and warehouse load. Cheong (2013) studied the effect of trans-shipments between retailers on their inventory replenishment actions for perishable food in a single-period planning horizon in a collectively controlled organization that operates many retail stores, managing their replenishment strategies together with the use of trans-shipments for two-period-life perishable goods. Tiacci and Saetta (2011) analyzed the relative effectiveness of two lateral shipment strategies in which the mean supply is delayed according to a traditional non-lateral shipment strategy in a two-echelon supply channel simulation experiment.

With the impact of the Covid-19 outbreak, interest in e-commerce has increased in the food supply chain. Therefore, Webster et al. (2006) examined developments during the adoption of e-business involving the fast-moving consumer goods (FMCG) sector in a UK soft drinks company. Their study presents detailed literature to define technological solutions to succeed in e-commerce; it also classifies the drivers and barriers related to its adoption. Also, Fritz and Canavari (2008) suggested that vertical food coordination and market relationships in supply chains can be defined as rapidly changing. Therefore, this study examines the decision preferences for prioritizing by using an analytic hierarchy process (AHP) in order to build trust, the base of the e-business design. Yu and Wei (2018) researched inventory management including lateral trans-shipment as well as quick response in an e-commerce supply chain. To that end, system dynamics have been examined by integrating quick response (QR) and lateral trans-shipment (LT), with a new inventory control strategy proposed as a result. Stritto and Schiraldi (2013) sought to address the difference between theoretical schemes or abstract structures and the practical challenges faced by logistics managers in supply chain management. This is because they need to move their food and beverage retail company into e-business while keeping a strong consistency with their existing approach.

This paper contributes to the lateral trans-shipment literature in two ways. First, we study an e-grocery order case where order sizes are small, there are expiration dates for food products and the network is fully connected. Second, due to an e-commerce application, we do not consider physical trans-shipment of products in the models; instead the items are shipped to the customers directly without making lateral trans-shipments. Not considering an extra delay for physical trans-shipment of products, the second issue contributes to both increased customer satisfaction and decreased average inventory carried in the network. This research further explores how B2B policy (i.e. lateral-inventory share policy) should be designed to optimize both business (i.e. supermarkets) profitability and sustainability in terms of minimizing overall food waste.

In the following sections, the problem under examination is detailed along with the considered inventory share scenarios and their simulation models.

3. Materials and methods

3.1. System description

This study evaluates systems for e-groceries selling food products connected in an IoT environment, where their inventories are visible to each other in real time. When a customer places a food order via a company's web site, that supermarket searches within the store and its connected supermarkets' existing inventories in terms of their closest expiration dates etc.; the best available product option is then selected and shipped to the customer. In this sense, using a shared inventory policy, also known as business-to-business (B2B) e-commerce models, one business makes a commercial transaction with another not only to assure an economic advantage, but also to develop a sustainable food network.

This research aims to explore how B2B policies (i.e. lateral-inventory share policies) should be designed for business (i.e. supermarkets) profitability, sustainability of minimizing overall food waste, determining average inventory carried in the network and other performance metrics. To achieve this, we develop an experimental design table including different factors that could affect those inventory system performance metrics. Specifically, instead of looking at cost related parameters, the performance metrics of the systems are evaluated in terms of average food inventory carried, amount of food waste, frequency of lateral inventory share and ordering from the main depot; customer service level (CSL) in the network is also assessed. It would be difficult to define unit cost parameters correctly and any results obtained would be very sensitive to the parameters selected. Thus, instead of defining the system performance metrics based on costs, we consider and observe the network parameters in terms of frequency or amount.

In the e-grocery purchasing case, we consider a single-echelon food supply chain network including three online groceries served by a main depot. Fig. 1 shows the studied network. Each online grocery has its own demand inter-arrival time distributions. In Fig. 1, dashed lines show information flows while solid lines show physical product flows. Customers place orders via the online grocery's web site. Here, orders are perishable food orders. We assume that there are three types of perishable food products whose shelf lives are different from each other. When the expiration date of a product passes, then the status of that food product becomes food waste and it is thrown away.

We study an (s, S) inventory control policy for each online grocery based on the product types. Our aim is to find out the optimal (s, S) levels for each product type in each grocery. The studied food supply system is complex. It includes food shelf lives, dynamic inventory share policies as well as continuous replenishment (i.e. real-time checking of s, S inventory control policy) policies developed on current inventory levels. Besides, we consider multi-objectives to optimize which are: average inventory carried, ordering frequency from the main depot as well as customer service level of the network. Developing a closed-form solution, under such multi-objective case, stochastic demand and lead time as well as real time inventory control policy (i.e., s, S) would be hard and might led us to simplify those real system assumptions. Therefore, we simulate the systems by using ARENA 16.0 commercial software and complete a simulation-based optimization approach. A further aim is to understand how some performance metrics such as average inventory carried, total food waste amount, lateral inventory share amount, ordering frequency from the main depot in the network, etc. are affected, based on different inventory share policies. We also compare all the optimal results with the system results where there is no lateral inventory share in the network. The simulation model details along with the considered assumptions are explained in the next section.

3.2. Simulation model assumptions

As mentioned earlier, a simulation modeling method is utilised to observe the behavior of the business models with different lateral inventory share rules as well as the model without inventory share rule in the system. The appropriate re-order and up-to inventory levels (i.e. s, S levels) are determined by using the *OptQuest* optimization tool provided in the ARENA 16.0 simulation package. The online grocery network is simulated with the assumptions outlined as follows:

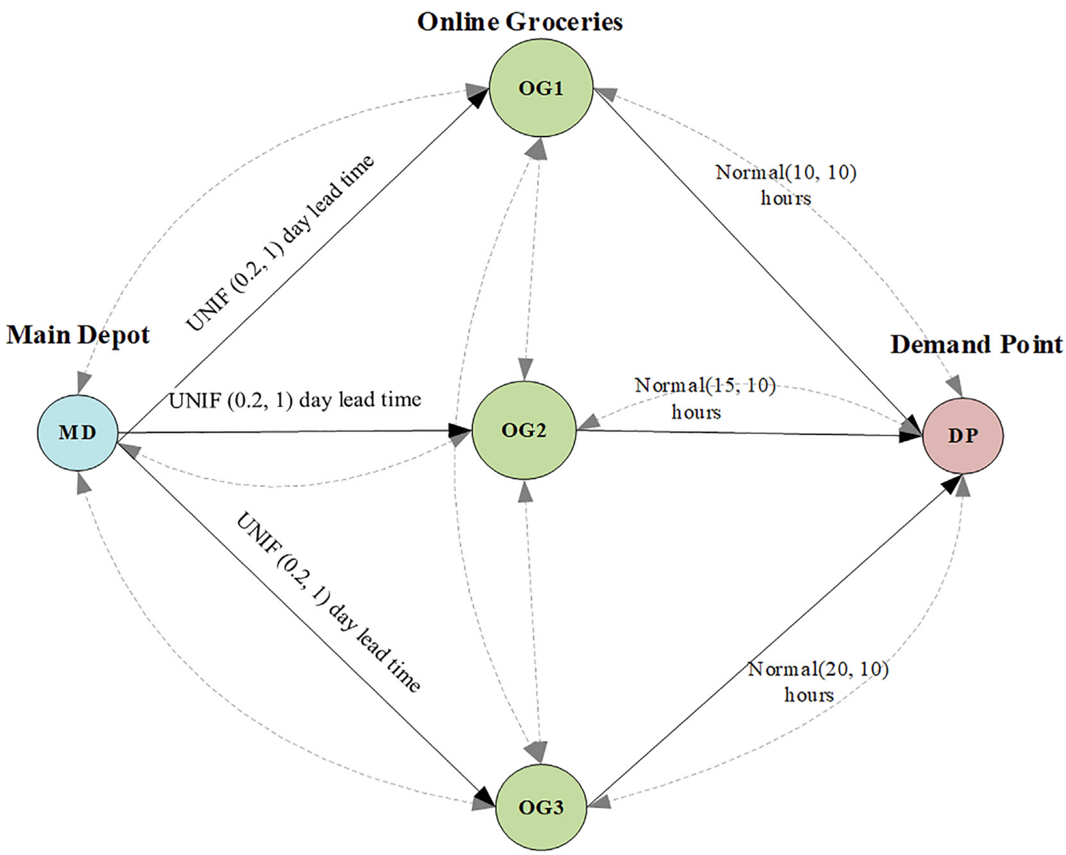

Fig. 1. The studied online grocery network.

- Three online groceries selling perishable food products at the same echelon are considered (see Fig. 1).
- There are three types of food products at each online grocery; shelf lives are considered to be 5, 7 and 10 days in the one scenario and 7, 10 and 12 days in another scenario for their product types respectively.
- By assuming that the case is online ordering in e-groceries, the ordered items are accumulated so that the companies ship the orders 1–3 times a day, we set the demand inter-arrival distributions as normal (10, 10), normal (15, 10) and normal (20, 10) hours for the first, second and the third online groceries, respectively.
- The probability distribution for each type of food product arrived at any grocery is the same (with 1/3 probability level).
- Mean amount of demand for a product type arriving at a grocery follows uniform distribution with mean and standard deviation as (15, 30).
- A continuous (s, S) inventory control policy is utilised for the inventory review policy. In that policy, an online grocery places an order from the main depot, by continuously reviewing its current inventory level. If its inventory level decreases to a level less than s, then an order quantity is placed to raise the current inventory to an order-up-to level of S.
- The food product requirements of online groceries are satisfied by a main depot having infinite capacity.
- Lead time from the main depot to each online grocery follows uniform distribution with parameters (0.2, 1) days.
- The probability of back ordering is assumed to be 15%. This means that if the entire amount of demand cannot be met by the online groceries, with 15% probability the remaining amount would be met by future products arriving from the main depot. Otherwise, it would be a lost sale or opportunity.
- It is aimed to achieve at least 95% customer service level in the optimization procedure.
- The simulation model is to run for one year. The warm-up period is one month.
- Ten independent replications are performed.
- Verification and validation of the simulation models are carried out by debugging the codes and animating the system.

3.3. Notations and pseudo-codes considered in the simulation models

The notations that are used in the simulation models are provided below:

DF total number (frequency) of demand arrivals in the network during the simulation run.
FW total amount of food waste in the network during the simulation run.
LT total amount of food product met by lateral inventory share in the network during the simulation run.
TF total amount of food products sent from the main depot to the online groceries in the network during the simulation run.
sST total number of replenishment in the network during the simulation run.
LS_i total amount of lost sales at online grocery i during the simulation run, $i = \{1, 2, 3\}$.
TD_i total amount of demand arriving at online grocery i during the simulation run, $i = \{1, 2, 3\}$.
CSL_i customer service level at online grocery i during simulation run (e.g. calculated by (1)).
SL_j shelf life of food product type j, $j = \{1, 2, 3\}$.
I_{ijkt} inventory level of product j, at online grocery i, having k remaining days until its expiration date at time $t, i = \{1, 2, 3\}$, $j = \{1, 2, 3\}$, $k = \{1, \ldots, SL_j\}$.

I_{ijt} total inventory level of product j at online grocery i at time t, $i = \{1, 2, 3\}$, $j = \{1, 2, 3\}$.
s_{ij} re-order level for product type j, at online grocery i, $i = \{1, 2, 3\}$, $j = \{1, 2, 3\}$.
S_{ij} up-to level for product type j, at online grocery i, $i = \{1, 2, 3\}$, $j = \{1, 2, 3\}$.
D_{ijt} amount of demand for product type j arrived at online grocery i, at time t, $i = \{1, 2, 3\}$, $j = \{1, 2, 3\}$.
q_{ijt} order amount for product j demanded from the main depot at online grocery i at time t, $i = \{1, 2, 3\}$, $j = \{1, 2, 3\}$.
AIL time-persistent average inventory level in the network during the simulation run
CSL customer service level of the network (e.g. calculated by Eq. (2))
FWR food waste ratio in the network (e.g. calculated by Eq. (3))
LTR lateral inventory share ratio in the network (e.g. calculated by Eq. (4))
OFR order frequency ratio from the main depot in the network (e.g. calculated by Eq. (5))

Some of the calculations that are completed at the end of the simulation runs are summarised by Eqs. (1)–(5). For instance, customer service level at online grocery i (CSL_i) is calculated by (1). Here, CSL_i is the ratio of demand met by online grocery i to the total demand arriving at online grocery i. Hence, customer service level of the network is calculated by averaging the values of CSL_i for online groceries as shown by Eq. (2).

$$CSL_i = 1 - \frac{LS_i}{TD_i} \tag{1}$$

$$CSL = \frac{\sum_{i=1}^{3} CSL_i}{3} \tag{2}$$

Food waste ratio in the network is computed by Eq. (3). This is the ratio of the total amount of food waste in the network during the simulation run to the total amount of food products sent from the main depot to the online groceries in the network during the simulation run:

$$FWR = \frac{FW}{TF} \tag{3}$$

Lateral inventory share ratio in the network is computed by Eq. (4). It is the ratio of the total amount of food products met by lateral inventory share in the network during the simulation run to the total amount of demand that could be met by the network:

$$LTR = \frac{LT}{\sum_{i=1}^{3} (TD_i - LS_i)} \tag{4}$$

Order frequency ratio in the network is computed by Eq. (5). It is the ratio of the total number of replenishments in the network during the simulation run to the total number (frequency) of demand arrivals in the network during the simulation run.

$$OFR = \frac{sST}{DF} \tag{5}$$

Algorithm 1 shows the pseudo-codes presenting how simulation of the (s, S) inventory control policy and the replenishment process of the systems are modelled in the software. Briefly, the inventory control model is a continuous review policy, meaning that when the current inventory level of any food product in any grocery I_{ijt} drops below its re-order inventory level s_{ij}, the replenishment process starts. Sufficient amount of food products q_{ijt} are ordered from the main depot to increase the inventory level up to its up-to inventory level S_{ij}. When the order arrives at the grocery, that grocery's current inventory is increased by q_{ijt} amount. Remaining shelf lives are also updated at that point. Algorithm 2 shows the inventory update processes in the systems based on the expiration date. Note that these inventory level updates are completed at the end of each day. When the expiration date of a food product passes, then that amount of inventory is decreased based on the amount spoiled.

Algorithm 1. The s, S inventory control policy and the replenishment process in the systems

```
Ensure i = 1//online grocery
Ensure j = 1 //type of food product
  while i <= 3 do
    while j <= 3 do
      if i_ijt <= s_ij then
        q_ijt = S_ij - I_ijt
        sST = sST + 1
        Delay with UNIF (0.2, 1) day
        //lead time considered from the main depot
        I_ijt = I_ijt + q_ijt
        Update I_ijkt: I_ijSL_jt = I_ijSL_jt + q_ijt
        TF = TF + q_ijt
      end if
      j = j+1
    end while
    i = i+1
    j = 1
  end while
```

Algorithm 2. The inventory update process in the system

```
Ensure Start at the end of each day
Ensure i = 1 //online grocery
Ensure j = 1 //type of food product
Ensure k = 1 //remaining day for the expiration date
  while i <= 3 do
    while j <= 3 do
      while k <= SL_j do
        if k == 1 then
          FW = FW+ I_ij1t
          I_ijt = I_ijt - I_ij1t
          I_ij1t = 0
        else
          I_ij(k-1)t = I_ijkt
          I_ijkt = 0
        end if
        k = k+ 1
      end while
      j = j+1
      k = 1
    end while
    i = i+1
    j = 1
  end while
```

3.4. Lateral inventory share policies

In an effort to test how lateral inventory share policies affect the average food waste, average inventory levels as well as lateral and ordering frequencies, etc., we define three different lateral inventory share policies. In addition, we test the system with no lateral inventory share policy. Here, our aim is to observe which policy works better in terms of the considered performance measures in the network and to enlighten practitioners on how to develop efficient policies.

3.4.1. Policy without Inventory share

In this policy, we try out the system with no lateral inventory share. In this sense, our aim is to observe how a lateral inventory share policy affects the system performances compared to a non-inventory share policy. In this policy, each online grocery meets its demand from its existing inventories by considering the closest expiration dates of food products. In this policy, the online grocery does not check the others' levels. If there is not enough inventory available, then the remaining amount is considered to be lost sales with 85% (i.e. 15% back order) of probability level.

3.4.2. Lateral inventory share policy 1

Among three developed lateral inventory share policies, the first one is developed based on the closest expiration date of the food products. The lateral inventory share is completed by the food products having the closest expiration dates. This means that when an order arrives at an online grocery, it starts meeting the demand by the product having the closest expiration date from all the groceries. In this policy, no priority is given to a specific grocery; instead the priority is given to the food products that are near to spoilage.

3.4.3. Lateral inventory share policy 2

The second lateral inventory share policy is developed based on selecting a grocery to meet the demand. In this system, a grocery having the smallest average expiration date ratio for product j is selected to meet the demand for product j. Since having zero as the denominator would provide an undefined result, we treat the ratio as maximisation by inversing the calculation. First, with an expiration date-based ratio for grocery i, R_i, is calculated by Eq. (6). Then, the online grocery i having the maximum R_i, is selected to meet the demand. If all of the demand cannot be met by that grocery i, then, the second and the third maximum ratio groceries in order are selected to meet the remaining order.

$$R_i = \frac{\sum_{k=1}^{SL_j} \frac{I_{ijkt}}{k}}{\sum_{k=1}^{SL_j} n_k}, \quad i = \{1, 2, 3\} \tag{6}$$

For Eq. (6), the values that $n(k)$ can take are as follows:

$$n(k) = \begin{cases} 1, & \text{if} \quad I_{ijkt} > 0 \\ 0, & \text{otherwise} \end{cases}$$

3.4.4. Lateral inventory share policy 3

The last lateral inventory share policy is developed based on selecting a product j having k remaining days until its expiration date for grocery i. A ratio, R_{ijk} is calculated by Eq. (7). Then, the maximum R_{ijk} valued food product j at grocery i with k remaining days until its expiration date is selected to meet the demand. Here, our aim is to select the product j with the closest expiration date and the highest amount of inventory level at the same time. If all of the demand cannot be met by that product, then the second, third, fourth and so on, maximum ratio products in order are selected to meet the remaining order.

This is different from policy 2. In this policy, we do not select a single grocery, but instead select the highest ratio product based on expiration date and inventory level for each grocery. Thus, there can be more than one ratio for product j in a single grocery due to different expiration dates. By this policy, our aim is to decrease both the food waste ratio, *FW*, as well as the order frequency ratio from the main depot in the network, *OFR*.

$$R_{ijk} = \frac{I_{ijkt}}{k}, \quad k = \{1, \ldots, SL_j\} \tag{7}$$

The pseudo-code for the third lateral inventory share policy is shown in Algorithm 3. This shows that the selection of the lateral grocery for inventory share is based on the maximum R_{ijk}. Either all or I_{sjdt} amount of demand is met. This procedure continues until the entire amount of the remaining demand is met. If all demand cannot be met, then the customer is asked to wait, with 0.15% probability, for the next replenishment to be met (i.e. back order). Otherwise, lost sales, *LS*, occur.

Algorithm 3. Policy 3 inventory share policy

```
Ensure Start with every demand arrival
Ensure i = 1 //online grocery
Ensure k = 1 //remaining day until the expiration date
Ensure d = 1 //d is the remaining day of chosen product
Ensure s = 1 //s is the online grocery of chosen product
  cwt = DISC (0.15, 1; 0.85, 0)//customer waiting
  tolerance
  D_gjt = UNIF(15, 30) //g is the online grocery that
  current demand arrives, j is the arriving product type
  TD_g = TD_g+ D_gjt
  DF = DF + 1
  while i <= 3 do
    while k <= SL_j do
      I_ijt = I_ijt + I_ijkt
      Calculate the ratio R_ijk = I_ijkt/k
      if R_ijk > (I_sjdt/d) then
        d = k //the remaining expiration day of the
  chosen product
        s = i //the online grocery of the chosen product
          end if
          k = k + 1
        end while
      i = i+ 1
      k = 1
    end while
    if I_1jt+ I_2jt+ I_3jt< D_gjt and cwt == 1 then
      wait for (I_1jt+ I_2jt+ I_3jt) > D_gjt //Backordering
    end if
    if I_1jt+ I_2jt+ I_3jt >= D_gjt then
      if I_sjdt >= D_gj then
          I_sjdt = I_sjdt- D_gjt
        I_sjt = I_sjt - D_gjt
        if g<> s then
          LT= LT+ D_gjt //The original grocery where
  demand arrives
        end if
        D_gjt = 0 //Meet all the demand
    else
      D_gjt = D_gjt- I_sjdt //Meet Isjdt amount of demand
      I_sjt = I_sjt- I_sjdt
      I_sjdt = 0
    end if
  else
      LS_g = LS_g+ D_gjt //Lost sale
  end if
```

3.5. Simulation optimization

After simulating and validating each developed policy, we optimize the procedure by minimizing the time-based average inventory carried in the network. We consider the s_ij, S_ij levels as decision variables. For the optimization of each policy, we have utilised the OptQuest tool provided in the ARENA simulation software. The OptQuest optimization tool integrates mainly three metaheuristics. These are Tabu search (TA), Neural Networks (NN) and Scatter Search (SS) (Kleijnen and Wan, 2007). Users are allowed to define linear constraints for the simulation optimization. The tool uses the search procedure from the starting point required from the user perspective to specify the lower, suggested and the upper values for the decision variables (i.e. s, S levels) to be optimized. The effectiveness of this tool for optimization is advocated by Kleijnen and Wan (2007) for an (s, S) inventory model. The tool also summarizes what the so far best result is and, whether or not the last run results in a feasible solution. The calculations embedded in OptQuest for optimization of complex systems are explained in the next sections. We also show how this tool works with the algorithms in background.

3.5.1. OptQuest for optimization of complex systems

Many complex systems cannot be represented by a convenient mathematical model. To address this issue, optimization tools generally require assumptions simplifying the real system and definition of the problem.

When dealing with the optimization of complex systems, it is often difficult to develop a mathematical representation of the problem. Heuristic solution procedures are common approaches for such systems. However, since they are generally lacking in providing high quality solutions for complex problems, metaheuristics are developed to considerably improve the performance of simple heuristic procedures. Genetic Algorithms (GAs), Tabu search (TA), Simulated Annealing (SA) and Scatter Search (SS) are some examples of metaheuristics recently developed to solve complex optimization problems in different domains.

SS is the main approach for the optimization engine of OptQuest. It is also coupled with Tabu search strategies as well as neural networks to obtain high quality solutions for complex problems (Laguna, 2011). OptQuest was developed by the team of Glover, Kelly and Laguna at the University of Colorado (Glover et al., 1996). Currently, OptQuest can be used as an optimization engine in simulation software such as Arena, Promodel, Simul8, Simio and many others (http://www.opttek.com/Partners/).

3.5.2. OptQuest optimizer

As mentioned, the main optimization procedure in OptQuest is based on the SS metaheuristic. SS works to process the reference points constituting good solutions obtained from previous trials. In the algorithm, "good" stands for diversity seeking to go beyond the value of the objective function. In order to create new points, combinations of reference points are generated by the SS. Each new point combination is mapped as a feasible point.

SS is an $information-driven$ approach. It exploits the information derived from the search space (e.g. after simulation runs), good solutions found within the space etc. Such designs need to be incorporated to enable efficient searches of solution spaces in complex optimization problems.

Fig. 2 shows the SS approach. It includes three steps. Step 1 is to catch data not included in the tried points. Step 2 is to evaluate the combinations produced and to generate new points. Step 3 is to follow a strategy for reference setting instead of randomisation.

OptQuest searches for an optimal solution of a problem defined on bounded variables (a vector of x) (Laguna and Marti, 2003). The SS starts by generating a starting set of points. This is realised by dividing the range of each variable into four equal sized sub-ranges. Then, a two-step solution is constructed. In the first step, a sub-range is selected randomly whose probability of selection is inversely proportional to its frequency of selection. For that, the specific sub-range selected is counted. In the second step, a random value is selected from the chosen sub-range. The definition of initial starting points considers the solutions below (Laguna and Marti, 2003):

- Set all the values for the lower bound (l)
- Set all the values for the upper bound (u)
- Set all the values for the midpoints $x = l + (u - l)/2$
- User allowed other suggested solutions

A rounding procedure is considered for mapping the fractional values to the discrete variables. If there are linear constraints in the model, first the feasibility of new created points is tested. Later, the F(x) – objective function – and the G(x) – requirements – are evaluated. The constraints are shown as $Ax \leqslant b$. In the feasibility test, each constraint is checked to see whether or not they are satisfied. If any of the constraints are not satisfied, in an effort to find a feasible solution x^*, the OptQuest formulates and solves a linear programming problem whose objective is minimization of absolute deviation of x and x^*. This procedure is shown by Eqs. (8)–(12):

$$\text{minimize} D^- + D^+ \tag{8}$$

$$\text{subject to} Ax^* \leqslant b \tag{9}$$

$$x - x^* - D^- + D^+ = 0 \tag{10}$$

$$l \leqslant x^* \leqslant u \tag{11}$$

$$D^-, D^+ \geqslant 0 \tag{12}$$

Here, D^- and D^+ stand for negative and positive deviations of x^* from the point x, an infeasible point, respectively. The variable values are adjusted according to their closest bounds; they are rounded properly when no constraints are determined. Hence, infeasible points are regarded as: if x is larger than u, then x^* is equal to u; if x is smaller than l, then x^* is equal to l.

After a set of references is defined, to start the optimal solution search, a linear combination of reference solutions is implemented based on Eqs. (13)–(15). Here, the reference solutions are assumed to be x' and x'':

$$x = x' - d \tag{13}$$

$$x = x' + d \tag{14}$$

$$x = x'' - d \tag{15}$$

d is computed by Eq. (16):

$$d = r \cdot \frac{x'' - x'}{2} \tag{16}$$

r is a random number between 0 and 1. The quality of the two reference solutions combined defines the number of new solutions. For instance, when the combination is made from the best two reference solutions, up to five new solutions are generated. However, when the combination is made from the two worst solutions, only one solution is generated. A reference set is considered to be the starting point for new combination rounds.

In OptQuest the feasibility of x cannot be tested until the simulation run is completed. Fig. 3 illustrates that condition. According to the figure, when the optimization model includes constraints, by mapping $x \rightarrow x^*$, the process of evaluation is started.

The complex system evaluator processes the mapped solution. Then, performance measures are obtained. $F(x)$ is defined from those performance measures. It is used to separate good solutions

1. In order to build a solution set as a starting attempt, implement a diversification generation method (DGM). By evaluating their quality and diversity, define the reference points by a subset determined by the best points.

while (do until stopping criteria are met)

2. In order to create new points to evaluate, develop combinations of subsets of the reference points selected to produce points both inside and outside the convex region. In an effort to create feasible points based on the constraints in the problem, these combinations are modified by generalized mapping processes.

3. By considering the points improving the quality and/or diversity of the set, update the reference set.

if in the current set, no search can be completed for new combinations.

4. In order to use the new starting points in the new implementation, select and evaluate a collection from the best points of the current reference.

Fig. 2. Scatter search outline (adopted from Laguna and Marti, 2003).

from bad solutions. $G(x)$ represents the requirements for boundaries. In OptQuest $P(x)$ is the penalizing function for requirement violations. It is dynamically changed through the search depending on the proportion of the violation. Based on these considerations, we have used the OptQuest optimizer with the results discussed in Section 3.7.

3.6. Experimental ddesign

An experimental design table is developed to evaluate the performance of the online network (see Table 1). From Table 1, three design parameters are considered. These are lateral inventory share policies as defined in Section 3.4, order frequency ratio from the main depot in the network, *OFR* and shelf life for food product type 1, 2 and 3 (in days).

OFR was calculated by Eq. (5). In the $SL_{1,2,3}$ scenarios, we consider two levels as tight (T) and large (L). In design T, we assume that the products types 1, 2 and 3 have shelf lives of 5, 7, 10 days respectively. In design L, we assume that the products types 1, 2 and 3 have shelf lives of 7, 10 and 12 days respectively.

Table 1
Experimental design content.

Lateral inventory share policy	*OFR*	$SL_{1,2,3}$ (days)
1	0.30	Tight (5, 7, 10)
2	0.40	Large (7, 10, 12)
3		

From Table 1, we optimize each factor combination. Hence, we complete 12 ($3 \times 2 \times 2$) experiments and optimize them further. During optimization, we minimize the time-persistent average inventory level carried in the network (*AIL*). After establishing the optimal values for s_{ij} and S_{ij}, we run each model at these optimal points and summarise the results as shown in Table 2. We also observe the values of CSL, FWR, FW and LTR at the optimal points to compare each design.

We do not consider cost related parameters. This means that instead of optimizing the network using total cost objective functions, we optimize with the help of network parameters in terms of frequency or amount. Specifically, ordering frequency from the main depot is considered for ordering cost; average amount of

Fig. 3. Evaluation for solution (adopted from Laguna and Marti, 2003).

inventory during the simulation run is considered for holding cost; lateral inventory share frequency is considered for lateral inventory share cost and food waste ratio and amount in the network are considered for food waste cost.

3.7. The OptQuest results

Remember that, we optimize the Table 1 experiments by using OptQuest. Table 2 provides the simulation results at optimal points for an average of ten independent replications along with their half widths at 95% confidence intervals.

Table 3 shows the optimal s_{ij} and S_{ij} levels obtained by the OptQuest tool. The results are given based on the experiments designed in Table 1.

Table 4 presents the experimented simulation results for the system when there is no lateral inventory share.

Table 5 shows the optimal s_{ij} and S_{ij} levels obtained by the OptQuest results of Table 4.

Screenshots from the OptQuest run, showing how we define the objective function, constraints and decision variables, etc. is shown by a figure given in the Appendix part as A.1. Note that since the decision variables in the optimization process are considered as the reorder and up-to inventory levels of each product type in each online grocery, 18 ($2 \times 3 \times 3$) decision variables are determined in the optimization tool. Time-persistent average inventory carried in the network is minimized in the optimization. Further, in an effort to reduce the ordering frequency from the main depot, while assuring a desired *CSL*, we set them as constraints from a multi-objective perspective. The optimization model entered in the OptQuest tool is shown by Eqs. (17)–(20). According to that, the objective function is given by Eq. (17) considering the minimization of the time-persistent average inventory level carried. The constraints

Table 2
Optimization results for experimental design table.

#	Pol.	SL	OFR	AIL	CSL	FWR	FW	LTR
1	1	T	0.30	477 ± 4	$0.999 \pm 1 \cdot 10^{-3}$	$0.091 \pm 4 \cdot 10^{-3}$	$4,033 \pm 180$	$0.603 \pm 9 \cdot 10^{-3}$
2	1	T	0.40	304 ± 3	$0.977 \pm 2 \cdot 10^{-3}$	$0.032 \pm 5 \cdot 10^{-3}$	$1,285 \pm 184$	$0.615 \pm 8 \cdot 10^{-3}$
3	2	T	0.30	283 ± 4	$0.960 \pm 3 \cdot 10^{-3}$	$0.054 \pm 3 \cdot 10^{-3}$	$2,202 \pm 124$	$0.652 \pm 8 \cdot 10^{-3}$
4	2	T	0.40	264 ± 4	$0.955 \pm 4 \cdot 10^{-3}$	$0.052 \pm 5 \cdot 10^{-3}$	$2,097 \pm 176$	$0.655 \pm 9 \cdot 10^{-3}$
5	3	T	0.30	283 ± 5	$0.952 \pm 2 \cdot 10^{-3}$	$0.066 \pm 3 \cdot 10^{-3}$	$2,713 \pm 121$	$0.448 \pm 8 \cdot 10^{-3}$
6	3	T	0.40	257 ± 4	$0.952 \pm 3 \cdot 10^{-3}$	$0.057 \pm 3 \cdot 10^{-3}$	$2,307 \pm 144$	$0.445 \pm 7 \cdot 10^{-3}$
7	1	L	0.30	391 ± 4	$0.967 \pm 3 \cdot 10^{-3}$	$0.016 \pm 2 \cdot 10^{-3}$	627 ± 81	$0.588 \pm 9 \cdot 10^{-3}$
8	1	L	0.40	270 ± 3	$0.953 \pm 4 \cdot 10^{-3}$	$0.011 \pm 2 \cdot 10^{-3}$	440 ± 57	$0.550 \pm 7 \cdot 10^{-3}$
9	2	L	0.30	282 ± 4	$0.957 \pm 6 \cdot 10^{-3}$	$0.021 \pm 2 \cdot 10^{-3}$	829 ± 69	$0.658 \pm 6 \cdot 10^{-3}$
10	2	L	0.40	236 ± 4	$0.954 \pm 3 \cdot 10^{-3}$	$0.008 \pm 1 \cdot 10^{-3}$	326 ± 48	$0.636 \pm 9 \cdot 10^{-3}$
11	3	L	0.30	292 ± 4	$0.957 \pm 7 \cdot 10^{-3}$	$0.027 \pm 2 \cdot 10^{-3}$	$1,079 \pm 79$	$0.440 \pm 6 \cdot 10^{-3}$
12	3	L	0.40	262 ± 4	$0.952 \pm 6 \cdot 10^{-3}$	$0.021 \pm 1 \cdot 10^{-3}$	841 ± 41	$0.448 \pm 7 \cdot 10^{-3}$

Table 3
Optimal (s, S) levels for experimental design table.

#	(s_{11}, S_{11})	(s_{12}, S_{12})	(s_{13}, S_{13})	(s_{21}, S_{21})	(s_{22}, S_{22})	(s_{23}, S_{23})	(s_{31}, S_{31})	(s_{32}, S_{32})	(s_{33}, S_{33})
1	11, 105	0, 75	15, 90	5, 50	0, 70	0, 100	5, 40	8, 75	0, 55
2	0, 65	0, 20	0, 40	0, 65	0, 65	0, 95	0, 10	3, 105	0, 10
3	9, 60	1, 85	1, 70	7, 45	2, 80	12, 100	3, 45	1, 65	0, 75
4	10, 65	1, 75	1, 40	7, 45	2, 80	12, 105	3, 50	1, 60	0, 60
5	17, 60	1, 60	3, 65	0, 50	0, 85	6, 115	0, 65	1, 60	4, 75
6	15, 60	5, 60	5, 60	0, 50	0, 80	5, 90	0, 60	5, 50	5, 60
7	0, 175	0, 80	0, 70	0, 10	0, 45	0, 90	0, 10	0, 75	0, 45
8	0, 155	0, 70	0, 60	0, 10	0, 20	0, 40	0, 10	0, 65	0, 25
9	20, 70	3, 45	14, 80	0, 55	0, 30	6, 120	21, 85	13, 70	0, 25
10	19, 60	3, 45	14, 11	0, 30	0, 35	4, 105	19, 35	13, 60	0, 30
11	18, 55	2, 90	10, 70	15, 75	0, 55	10, 105	15, 55	5, 55	9, 75
12	15, 60	2, 90	10, 60	14, 60	0, 35	8, 90	15, 50	5, 55	8, 75

Table 4
Optimization results when there is no lateral inventory share.

#	SL	OFR	AIL	CSL	FWR	FW
1	T	0.30	787 ± 5	$0.954 \pm 5 \cdot 10^{-3}$	$0.416 \pm 7 \cdot 10^{-3}$	$27,377 \pm 373$
2	T	0.40	579 ± 4	$0.953 \pm 4 \cdot 10^{-3}$	$0.280 \pm 7 \cdot 10^{-3}$	$14,980 \pm 341$
3	L	0.30	583 ± 4	$0.997 \pm 6 \cdot 10^{-3}$	$0.275 \pm 6 \cdot 10^{-3}$	$15,390 \pm 362$
4	L	0.40	283 ± 3	$0.968 \pm 5 \cdot 10^{-3}$	$0.210 \pm 5 \cdot 10^{-3}$	$10,422 \pm 287$

Table 5
Optimal (s, S) levels when there is no lateral inventory share.

#	(s_{11}, S_{11})	(s_{12}, S_{12})	(s_{13}, S_{13})	(s_{21}, S_{21})	(s_{22}, S_{22})	(s_{23}, S_{23})	(s_{31}, S_{31})	(s_{32}, S_{32})	(s_{33}, S_{33})
1	50, 130	50, 130	50, 130	50, 130	50, 130	50, 130	46, 130	50, 130	48, 130
2	41, 80	46, 90	41, 100	35, 90	39, 90	38, 100	39, 100	34, 90	45, 110
3	43, 135	17, 60	20, 80	0, 90	14, 110	7, 135	3, 85	2, 125	0, 85
4	0, 85	0, 55	7, 40	0, 80	0, 65	0, 85	0, 50	0, 55	0, 75

are shown by Eqs. (18)–(20). Since frequent replenishment would be inefficient in terms of sustainability and cost, *OFR* is limited to 0.30 or 0.40 as defined in the experimental design table shown in Section 3.6. The desired *CSL* is defined to be at least 95% level, meaning that customer satisfaction is guaranteed to a degree of at least 95%.

$$\text{minimize} AIL \tag{17}$$

$$\text{subject to} CSL_i \geqslant 0.95 \quad CSL_i \in R^+, \quad \forall i \tag{18}$$

$$s_{ij} < S_{ij} \; s_{ij}, S_{ij} \in Z^+, \quad \forall i, \forall j \tag{19}$$

$$OFR \leqslant 0.30 \text{ or } 0.40 \quad OFR \in R^+ \tag{20}$$

We summarise our findings from the simulation optimization results in the next section.

4. Discussions and implications for managers

As expected, one of the most attractive results for a food supply network is that a network design allowing a shared inventory policy works better in terms of food waste as well as average inventory carried in the network compared to a design when there is no lateral inventory share. Specifically, we observed that total food waste in the network decreases significantly by an inventory share policy, especially when the food shelf life is tight. Hence, inventory share design policies for tight food shelf life products are worth consideration.

Also, at the optimal points of the considered policies, lateral inventory share ratio is usually observed to be larger than 50% on average, meaning that more than half of customer order amounts are met by lateral inventory share. Thus, developing inventory share policies in e-commerce markets where customer orders are shipped to the customer locations directly without making a physical lateral trans-shipment between stocking facilities becomes a very significant issue. This will decrease transportation delays as well as increase customer satisfaction.

The important findings of this research are summarised as follows:

- The most attractive result from the optimal results is observed when Table 2 is compared with Table 4. This shows that there is significant improvement in terms of AIL, FWR and FW when there is lateral inventory share in the system compared to when there is no lateral inventory share. This means that food waste decreases drastically when any lateral inventory share policy is implemented into the system.
- Food waste decreases when order frequency ratio from the main depot in the network, *OFR*, increases. Thus, when the network is allowed to order more frequently from the main depot, the *FWR* and *FW* decreases. This is because when the *OFR* is tight, the groceries tend to carry a large inventory so as not to ruin the ordering frequency constraint (0.3 or 0.4), resulting in increased spoilage/wastage of food products. Supply chain m anagers should therefore focus on decreasing the ordering cost, and hence increasing the ordering frequency from the main depot; this would increase the overall efficiency of the network.
- As expected, when the shelf life of food products is tight, *FWR* and *FW* values tend to increase drastically compared to the experiments conducted with a large shelf life of food products. It was noted that more food waste happens in the network when the shelf life of products is tight. So, all three of our proposed inventory policies would be useful for managers and practitioners in maintaining appropriate inventory levels for products having large shelf lives (e.g. larger than 7, 10, 12 days); this further helps in reducing food waste. In addition, the proposed inventory policies can also guide managers and members to build robust lateral inventory share policies considering expiration date scenarios and food waste management. It is observed that generally, inventory share policy 2 works better in terms of *FWR* and *FW*. However, policy 3 works better in terms of *LTR*. This might be due to the fact that the second policy tends to meet customer demand from a single grocery having minimum average shelf life from product i, SL_i, based on a ratio developed on product i's inventory amount as well. However, the third policy only considers a ratio based on product type i over its inventory level. It does not strongly consider the small shelf life product as policy 2 does. Hence, in policy 3 the possibility would be high that food spoilage could occur compared to policy 2.
- When there is no lateral inventory share in the system, increasing order frequency from the main depot helps in decreasing the total food waste in the network. With this policy, it is also observed that when the expiration date scenario is large, optimal safety stock levels tend to decrease. Otherwise, this level tends to increase. Thus, when there is no lateral inventory share in such a food supply network, the chain manager should focus on how to decrease ordering costs from the main depot so that more frequent orders with decreased order sizes can be placed; this would also result in decreased food waste in the network.
- Generally, when there is any lateral inventory share policy in the network, the groceries tend to carry a very small amount of safety stocks, which is related with decreased re-order levels, s, compared to a system when there is no lateral inventory share. This is probably because when there is no lateral inventory share in the system, uncertainty in groceries (mostly about demand or lead times) could be altered by carrying a safety inventory to meet desired *CSL*. However, in designs where there is any lateral inventory share, that uncertainty could be altered by lateral usage of inventory shares. Besides the safety stock, average inventory levels carried in the network are also generally low compared to the policy with no lateral inventory share.

5. Conclusion

During the recent pandemic lockdowns, the trend to online food purchasing has increased drastically; a safe and secure food supply has become one of the most critical issues for our society. With recent IT developments, real time tracking of information and data has been made possible. Hence, developing efficient B2B designs on inventory-share decisions optimizing both profitability and sustainability of e-commerce food businesses and customer satisfaction in the network might be one of the starting points in managing that critical issue.

In this work, we aim to shed a light on developing B2B models for connected, digitised e-grocery supply network designs to contribute to both customer satisfaction and sustainable food supply chain networks. To the best of our knowledge, this paper is an initial attempt in studying inventory share-based B2B models for e-grocery networks where customer orders are shipped to the customer locations directly without making a physical lateral trans-shipment to another online grocery. In addition, we aim to contribute to sustainable food supply chain literature by optimizing each pre-defined inventory share policy under a (s,S) inventory control model for different network designs (e.g. ordering frequency from the main depot, shelf life of food products, etc.) resulting in decreased food waste and increased sustainability in the network. Here, sustainability is achieved through profitability, decreased food waste and decreased transportation frequency from the main depot in the network. In order to achieve that target, we develop three inventory share models and implement a simulation-based optimization solution procedure by using ARENA 16.0 commercial software. We also optimize the network when there is no lateral inventory share in the network. The results show that there is significant improvement in terms of food waste as well as average inventory carried in the network when there is any pre-defined lateral inventory share in the network compared to a non-shared one. However, it is also observed that based on the developed inventory share policy, different performance metrics (e.g. food waste, ordering frequency from the main depot, average inventory carried in the network, lateral inventory share frequency, etc.) could be improved even more. For instance, when one policy might improve the lateral inventory share frequency, another might decrease food waste and contribute to sustainability. It is further observed that other design parameters of the system such as ordering frequency and shelf life of products also have a significant effect on the results. Therefore, more inventory share policies under different network design parameters (i.e. considered as constraints) also including shelf life conditions could be explored to test the behavior of the network.

For future research, more lateral inventory share policies by including more design parameters such as cost, truck capacity, lead time for delivery etc. could be explored. Besides, the design levels for expiration dates of products could also be enhanced; more frequent demand arrivals could be explored further. The system considers random arrivals, order amounts, lead times etc. and those random variables are defined by some specific distributions as stated in the assumption. Thus, the effect of uncertainty in the network in terms of demand inter-arrivals, their quantity, lead time variances and shelf life of products can also be tested more deeply to study the system behavior.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Banu Yetkin Ekren: Conceptualization, Methodology, Writing - original draft, Formal analysis. **Sachin Kumar Mangla:** Conceptualization, Writing - original draft, Supervision. **Ecem Eroglu Turhanlar:** Formal analysis, Data curation, Software, Validation. **Yigit Kazancoglu:** Investigation, Project administration, Writing - original draft. **Guo Li:** Conceptualization, Writing - review & editing.

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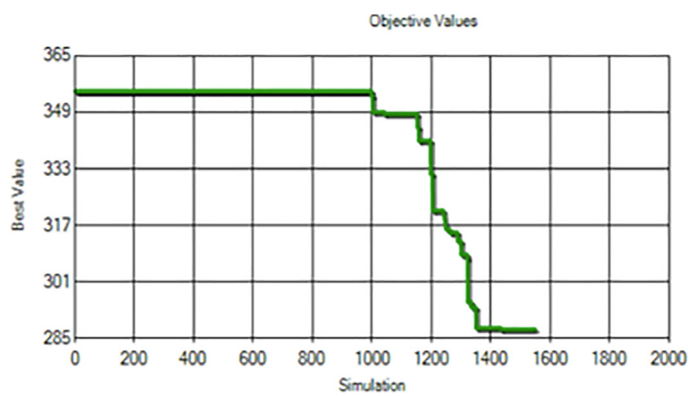
Appendix A

Fig. A1.

(i)

Constraints Summary		
Name	Type	Expression
Constraint 14	NonLinear	[Lateral Transshipment Ratio]<0.50
Constraint 15	NonLinear	[Order Frequency] <= 0.40
Constraint 1	NonLinear	[csl 1] >= 0.95
Constraint 10	Linear	[sLevel[3,1]]<[BigSLevel[3,1]]
Constraint 11	Linear	[sLevel[3,2]]<[BigSLevel[3,2]]
Constraint 12	Linear	[sLevel[3,3]]<[BigSLevel[3,3]]
Constraint 13	NonLinear	[Food Waste Ratio] <= 0.15
Constraint 2	NonLinear	[csl 2] >= 0.95
Constraint 3	NonLinear	[csl 3] >= 0.95
Constraint 4	Linear	[sLevel[1,1]]<[BigSLevel[1,1]]

(ii)



Optimization **Running**

Minimize			
		Objective Value	Status
	Best Value	287.524720	Feasible
	Current Value	388.783413	Infeasible

Best Simulation 1434
Running Simulation 1553
Replication 1 of 10

(iii)

Controls Summary								
Included	Category	Name	Element	Type	Low	Suggested Value	High	Step
☑	User Specified	BigSLevel[1,1]	Variable	Discrete	10	60	200	5
☑	User Specified	BigSLevel[1,2]	Variable	Discrete	10	60	200	5
☑	User Specified	BigSLevel[1,3]	Variable	Discrete	10	65	200	5
☐	User Specified	BigSLevel[1..3,...	Variable	Array	0	0	0	N/A

(iv)

Objectives Summary				
Name	Type	Goal	Description	Expression
Objective Function	NonLinear	Minimize	Minimization of Average Inventory	[Avg Inventory1] + [Avg Inventory2] + [Avg Inventory3]

Fig. A1. OptQuest screenshots: (i) constraint definition part, (ii) visualized optimization results, (iii) control part of the decision variables, (iv) objective function definition part.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.cor.2021.105237.

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